A Novel Model for Prediction of Wear and Coefficient of Friction Characteristics of Glass Fibre Reinforced Polytetrafluoroethylene Composites

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ARTICLE INFO

Article History
Received: 11 November 2022
Accepted: 12 September 2023
Published: 19 August 2024

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ABSTRACT

In this paper, two linear (weighted and simple averages) and two non-linear (neural network and support vector) ensemble models were built by integrating the responses of the two nonlinear models namely feed forward neural network (FFNN) and support vector regression (SVR) and one multilinear regression (MLR) model to improve the efficiency of single models in estimating the wear and coefficient of friction (COF) characteristics of glass fibre reinforced Polytetrafluoroethylene composites. The nonlinear models were found to increase the efficiency of single MLR model to at least 25% and 35% for wear and COF, respectively. It was found that SVR ensemble model was most robust by increasing the wear prediction efficiency of MLR, SVR, and FFNN single models to 45.19%, 27.23% and 9.77%, respectively. However, for COF it was seen that FFNN ensemble model was superior to other single models with increase of 39.00% for MLR, 4.05% for SVR and 5.05% for FFNN. These novel models hold potentials of saving cost and time in the study of wear and COF characteristics of FRPCs.

Keywords: *Prediction · Wear Characteristics · Linear Model · Nonlinear Model · Ensemble Model*

1. Introduction

Reinforcing of polymers with fibres has been identified as one of the effective methods of producing fibre reinforced polymer composites (FRPCs) suitable for light-weight and high strength applications [1]. Polytetrafluoroethylene (PTFE) is a preferred matrix in FRPCs productions owing to its heat stability, resistance to chemical attack and ease of production [2-3]. However, it shows lower wear characteristics [4]. It is usually reinforced with carbon, bronze and glass fibres [5-6] to improve its wear characteristics [7-8]. Therefore, it is necessary to study wear characteristics of FRPCs for existing and new applications. Wear characteristics are complex (nonlinear) [9-10] because many parameters such as material constitutions and experimental conditions [11-12] are involved. At present, artificial neural network (ANN) is receiving more attention for the building of prediction models via artificial intelligence (AI). ANN models are fast in supplying results and have indicated ability to handle complexity/nonlinearity [13] unlike conventional models which are poor at dealing with complexity/nonlinearity [14] of RFPCs. ANN is an example of artificial intelligence models that mimics the biological human system. It is made up of interconnected neuron with some nonlinear functions.

Jones, Jansen and Fusaro (1997) pioneered the application of ANN in the prediction of wear behaviour of rub shoe, pin-on-disk and four-ball rig [15]. Later, Velten, Reinicke and Friedrich (2000) compared ANN and multilinear regression (MLR) to predict wear rate of short carbon and glass FPCs. They found that ANN model produced better prediction than MLR model [16]. To establish best learning algorithms for the prediction of specific wear volume of discontinuous FRPCs, Zhang, Friedrich and Velten (2002) studied five different training algorithms of the ANN. It was observed that the various learning algorithms yielded dissimilar results for dissimilar problems. Better prediction efficiency was obtained at learning algorithm of 88% [17]. ANN is not limited to prediction of wear characteristics of FRPCs. Jiang, Zhang and Friedrich (2007and Jiang et al. (2008) predicted the mechanical properties and wear characteristics of FRPCs using ANN [18] and [19], respectively. Varade and Kharade (2012) predicted the specific wear of glass-fibre reinforced PTFE composites using ANN and Taguchi models. It was observed that ANN model gave better prediction than Taguchi model. Many studies were performed and proposed the correlation of wear characteristics model [20]. Abdelbary, Abouelwafa and Fahham (2014) worked on wear rate of pre-cracked nylon 66 using ANN different learning algorithms, number of hidden layers and neurons. It was revealed that best results were obtained with Levenberg-Marquardt learning algorithm, three layers and 20-10-10 neurons in the hidden achieving a prediction performance of 0.9910 [21]. Aleksendrić and Barton (2009) and Aleksendrić and Duboka (2006) estimated the wear rate of brake pad by training various ANN configurations and learning algorithms. They found that the best prediction adequacy was best results of ANN structure having 2 layers, 8 neurons in the first layer, 4 neurons in the second layer and, 5 neurons in the second layer and 10 neurons in the first hidden layer trained by Bayesian regularization training algorithm, [22-23], respectively. Aleksendrić and Duboka (2007) used ANN in the prediction of friction material at room temperature. They reported that better performance was achieved with a single hidden layer using Bayesian regularization learning algorithm [24]. Gyurova, Miniño-Justel, and Schlarb (2010) predicted the friction and wear rate of polyphenylene sulfide composites using ANN. In order to eliminate unnecessary neurons in the ANN architecture, an optimal brain surgeon technique was introduced so that the training computational cost was reduced and prediction performance of the ANN model enhanced. The results showed consistency with experimental results [25]. Hiral and Piyush (2019) used ANNs in the prediction wear characteristics of FRPCs [26].

Study of wear and friction coefficient characteristics of fibre reinforced polymer composites (FRPCs) is expensive and slow. A novel model which is cost and time-effective for prediction of wear and friction coefficient characteristics is thus significant. Therefore, the objective of this paper is to propose a novel model for predicting the wear and friction coefficient characteristics of glass fibre reinforced PTFE composites.

2. Method

Nonlinear AI models had demonstrated tremendous power in describing complex phenomena like wear and coefficient of friction. In this study, wear and coefficient of friction of reinforced glass fibre PTFE composite were modelled and predicted using FFNN and SVR and multi linear regression (MLR) models with density, volume fraction of the glass fibre, sliding distance, sliding speed and load as input factors while wear and coefficient of friction behaviour as outputs. PTFE is a synthetic fluoropolymer of tetrafluoroethylene that possesses superior characteristics due to its molecular structure consisting of fluorine and carbon. PTFE is hydrophobic and exhibits low wear resistance and it is soft in nature putting it at disadvantage [27]. Glass fibre (GF) is a material consisting of several fine fibres of glass. GF is less brittle, less strong and cheaper than carbon. GF is compatible with most of the synthetic resin, does not rot and remain unaffected by the action of rodents and insects.

2.1 Data Gathering and Description

The data used in this study had been extracted from the works of [28-29]. The two independent datasets have different materials constitutions at various wear testing conditions were used to train and test the FFNN, SVR and MLR models. Table I gives a descriptive statistic of the dataset used in this study. MATLAB 2019b and Minitab 2017 Toolboxes were used for developing the AI and the MLR models, respectively.

Table1. Descriptive statistics of the data used

Variable	Unit	Symbol	Minimum	Maximum	Average	Std. Dev.	Std. Error
Load	N	L	5	30	17.9661	9.2438	1.2034
Distance	m	D	1152	6000	3391.46	157.84	204.64
Speed	ms^{-1}	S	0.32	5.1836	2.0153	1.6667	0.2161

Volume fraction	%	V	0	20	9.9492	8.7186	1.1351
Density	gcm^{-3}	ρ	2.14	3.56	2.44	0.49	0.06
Wear	$gN^{-1}mm^{-3}$	-	0.12	830.12	104.3724	175.51	22.8611
COF	-	-	0.1	0.79	0.3273	0.1812	0.0236

2.2 Feed Forward Neural Network (FFNN) Model

FFNN is at present used to solve a vast of scientific and engineering problems [30]. ANN's ability to learn by example makes it important for simulation of any relation which is difficult to model using mathematical methods or any physical model [31]. Ideal prediction is often possible by ANN; ANN can be applied to make relatively good predictions in a number of conditions. Feed forward neural network (FFNN) as a type of ANN has been mostly applied to prediction purposes [32]. In a FFNN, the information is transmitted from the inputs of the network to them outputs without feedback between output layer and input layer. Figure 1 depicts architecture of a FFNN. A FFNN can consist of more than one hidden layer [33-34]. FFNN is an uncomplicated network that can be trained with back-propagation (BP) algorithm [35-37]. The BP algorithm is an iterative gradient descent method that minimizes the mean squared error between the observed and the computed values. The. Inputs fed into the ANN are multiplied by adjusted weights and transmitted via an activation (transfer) function to generate the output [38]. Subsequently, a bias value is added to the summation of the product of inputs and weights in accordance with equation (Eq.) 1 [38].

$$y_i = \sum_{i=1}^{N} w_{ij}x_i + b_i \tag{1}$$

where y_i = output, x_i = input signal in i layer and wij = weight from unit i layer to unit j layer bi = bias. The tan-sigmoid nonlinear transfer function $f\ (y)$ used in this study is given as (Eq.2) [35]:

$$f(y) = \frac{1- e^{-2x}}{1+ e^{-2x}}. \tag{2}$$

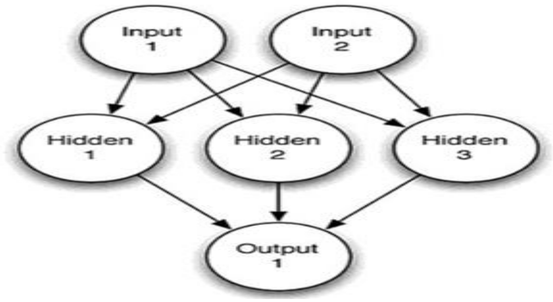


Figure 1. FFNN basic architecture

FFNN can be trained and optimized by various learning algorithms that perform better on different problems [19]. It is thus crucial that a suitable one is chosen. In this study, the FFNN was trained using different learning algorithms and only the best one is reported. Single layer is used in this work as it has been proved to approximate complex nonlinear function without complicating the network [23]. The tan-sigmoid transfer function was chosen due to its better performance over the other transfer functions [39]. Eq. 3 [40] was used to get the optimum number of neurons in the hidden layer instead of applying trial and error approach:

$$N_h \leq 2x_i + 1 \tag{3}$$

where N_h = number of neurons in the hidden layer whereas x_i =input.

2.3 Support Vector Regression (SVR) Model

Support vector regression (SVR) modelling deals with developing correlation between input and output variables. This machine learning method minimizes generalization problem [35, 41-42] and this makes it unique from other black-box based models. The principal purpose of SVR is to minimize errors between the actual and computed values. In this study, the inputs are the load, sliding distance, sliding speed, and volume fraction of the glass fibre and density of the materials while the outputs are the wear and the coefficient of friction of the PTFE glass-fibre reinforced composite. Assuming a set of training data $\{(x_i, y_i)\}_i^N$ in which x_i, y_i and N are input vector, observed value and total number of data samples, respectively. It is postulated that in SVR model building the training and testing data should be non-dependent, uniformly distributed and dependent in accordance with unforetold yet constant fundamental function [43]. Thus, the general functional regression model (Eq. 4) is given by [44]:

$$y = f(x) = \omega\varphi(x_i) + b \quad (4)$$

Very small values of φ (close to zero) indicate the points inside the insensitive hyper-tube, but nonzero values belong to support vector group [45]. Eq. 5 [44] gives the final model of the SVR approach.

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) K(x, x_i) + b \quad (5)$$

Where (x, x_i) is the kernel function performing the nonlinear mapping into feature space and b is the bias term. The customarily kernel function used is the Gaussian Radial Basis Function (RBF) mathematically written as (Eq. 6) [44]:

$$K(x, x_i) = \exp(-\gamma \parallel X_1 - X_2 \parallel^2) \quad (6)$$

where γ = kernel parameter. The common architecture of SVR is shown in Figure 2.

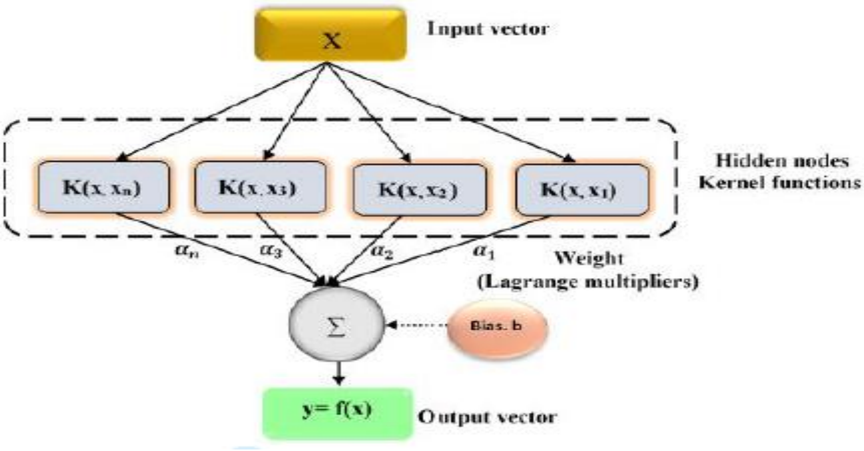


Figure 2. Conceptual configuration of SVR algorithm

2.4 Multi Linear Regression (MLR) Model

Linear regression analysis is a conventional technique used in applied science fields to describe and examine different parameters. Regression analysis especially aids in comprehending how the standard values of the dependent parameter varies as independent parameters vary, whilst the other independent parameters are held constant. It also examines the correlation between these parameters. The independent and dependent variables are related by Eq. 7 [40]:

$$y = \psi_o + \psi_1 x_1 + \psi_2 x_2 + \psi_3 x_3 + \cdots + \psi_i x_i \quad (7)$$

where y is the output (wear rate or COF) and x_1... x_i donate inputs (sliding speed, load, sliding distance, volume fraction glass fibre and density), ψ_o...ψ_i are the coefficients.

2.5 Data Pre-processing and Performance Evaluation

The output and input data need to be normalized before modelling. Data normalization is significant to make the interval value of the data convenient to the interval value of the chosen transfer function of the FFNN. The normalization as well takes care of dimensions and prevents bigger values from overshadowing smaller values. Hence in the pre-processing technique different interval in outputs and inputs must be normalized to a single interval. In addition to this, data normalization simplifies the numerical computations in the model that in turn raises the model accuracy and lowers the time it takes to achieve the global minimum. In this paper, normalization of the inputs and the output data was done in the range of 0 and 1 using Eq. 8 [27].

$$\lambda_{norm} = \frac{\lambda - \lambda_{min}}{\lambda_{max} - \lambda_{min}} \quad (8)$$

where λ_{norm} is the normalized wear and COF value, λ_{min}, and λ_{max} represent actual, minimum and maximum wear values of the data, respectively. The coefficient determination (DC) and the root mean square error (RMSE) were used as criteria in evaluating the prediction performance and efficiency of the models so developed. DC indicates fitness of the observed data and has values ranging from -∞ to 1. The closer the DC value to 1, the better is the prediction performance of the models and vice versa. RMSE is used to measure the difference between actual and predicted values. Lower value of RMSE signifies efficient models. The model having higher value of DC and low value of RMSE is the perfect model. The DC and RMSE are computed using Eq. 9 and Eq. 10, respectively [30].

$$DC = 1 - \frac{\sum_{i=1}^{n} (\lambda_{acti} - \lambda_{predi})^2}{\sum_{i=1}^{n} (\lambda_{acti} - \bar{\lambda}_{acti})^2} \quad (9)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\lambda_{acti} - \lambda_{predi})^2}{N}} \quad (10)$$

where the number of observations equals N, λ_{acti} stands for actual values, λ_{predi} represents the predicted values and $\bar{\lambda}_{acti}$ is the mean value of the actual values.

2.6 Ensemble Methods

Ensemble method is a machine learning method which is employed to integrate the process of many predictors so that the final performance of models is improved [46]. Raj and Ravi (2008) stated that there are two kinds of ensemble techniques namely: nonlinear and linear ensemble technique [47]. The former includes weighted median, weighted average and simple average and the latter deals with intelligence-based model like ANN, which is trained as a nonlinear kernel to get an ensemble response. SVM can alternatively be used for nonlinear ensemble method [48]. Utilization of this method in many engineering fields such as classification and clustering and web ranking has proved to improve the performance of single models [49-50]. These techniques overcome the complications of multiple-hidden-layered ANNs. Two nonlinear and two linear ensemble methods were developed for this study in order to improve on the performance of the single models for the prediction of wear behaviour and coefficient of friction of the PTFE composite. The general architecture of the ensemble method is shown in Figure 3.

2. 6.1 Linear Ensemble

2. 6.1.1 Simple Average (SA)

Here the arithmetic mean of the response factors (wear and COF) of the FFNN, SVR and MLR models is considered as the computed wear and coefficient of friction values as Eq. (11) [48]:

$$\bar{N} = \frac{1}{N} \sum_{i=1}^{n_m} N_i \quad (11)$$

where $\bar{N}$ is the result of the simple average ensemble technique (wear and coefficient of friction), n_m stands for the number of models developed (in this paper, n_m = 3) and N_i = results of the ith model namely ANN, SVR as well as MLR.

2. 6.1. 2 Weighted Average (WA) Ensemble

In the weighted average (WA), the weighted average of the wear and coefficient of friction of the PTFE glass fibre reinforced composite is calculated by assigning specific weights to the outputs of the single models based upon their relative importance. The weight is given based on the DC of the output. WA is thus given by Eq. (12) [48]:

$$\overline{N} = \frac{1}{N}\sum_{i=1}^{n_m} w_i N_i \qquad (12)$$

where w_i stands for the applied weight on the output of the i^{th} model that can be found based on the prediction performance obtained by Eq. (13) [48]:

$$w_i = \frac{DC_i}{\sum_{i=1}^{n_m} DC_i} \qquad (13)$$

in which DC_i represents the performance efficiency of the ith single model.

2.6.2 Non-Linear Ensemble

2.6.2.1 Feed Forward Neural Network Non-linear Ensemble (FFNNNE)

As to the non-linear ensemble method yet other FFNN and SVR models were trained to execute non-linear averaging of the wear and friction coefficient values from the single models developed. The input layer of the ensemble method is fed by the output values of the single models, each regarded as an input parameter. The FFNN architecture was trained with a layer and optimal number of hidden layer neurons was determined using Eq. 3.

2.6.2.2 Support Vector Regression Non-linear Ensemble (SVRNE)

In the SVRNE, the outputs of the individual models are fed to the SVR and RBF kernel function was used to estimate the output of the SVRNE.

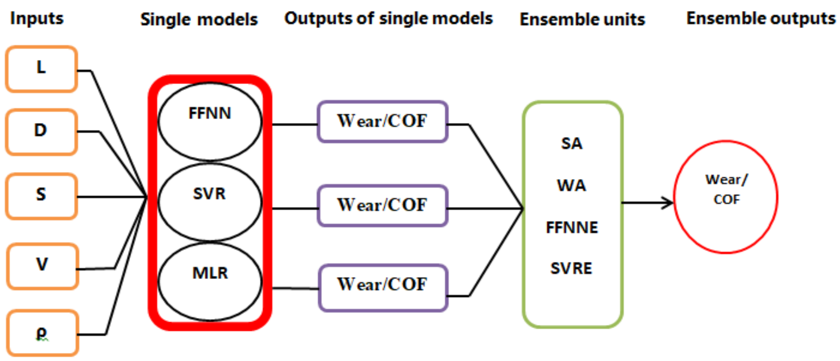


Figure 3. General ensemble methodology

3 Results and Discussion

Different learning algorithms perform well under different problems [23]. As such, it is important that the best algorithm is chosen. Based on the neural network toolbox of MATLAB 2019b, different learning algorithms were tried and only the optimum algorithms were reported and used for the performance prediction of wear behaviour and COF of the PTFE matrix composite. The prediction performance of the single and ensemble approaches was evaluated based on Eqs. 15 and 16. The prediction performance is sensitive to number of training datasets. As the number of training data decreased the prediction performance of the approaches is significantly reduced [17]. The results of the single approaches are presented in Table 2 and Table 3 for the wear and COF of the glass fibre reinforced PTFE composites, respectively.

3.1 Performance of the Single Models

Table 2. Wear performance results of the single models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
MLR	0.2960	0.1102	0.5473	0.2209
SVR	0.7409	0.0669	0.7267	0.1695
FFNN	0.9834	0.0169	0.9015	0.1017

Table 3. COF performance results of the single models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
MLR	0.6984	0.1677	0.5787	0.1053
SVR	0.9625	0.0591	0.9393	0.0456
FFNN	0.9696	0.0532	0.9321	0.0453

It can be seen from Table 2 that FFNN model trained by Bayesian regularization (BR) with architecture [5-11-1]1 and SVR having Gaussian radial basis function (RBF) predicted the wear of the glass fibre reinforced PTFE composites better than that of MLR model. The better prediction of FFNN DC (0.9015) and RMSE (0.1017) was due to the BR capability to provide shrinkage by using a penalty term that does away with unimportant parameters or posterior distribution of weights in or over the network, respectively [51] while that of SVR model DC (0.7267) and RMSE (0.1695) was due to its ability to first fit the data into linear regression prior to transmitting same to the nonlinear kernel function that handles the nonlinearity of the input data [52]. The lower prediction performance of the MLR model DC (0.5473) and higher RMSE (0.2209) is due to its inability to deal with nonlinear, noisy and complex relationship between input and output parameters [53-54] which are typical characteristics of the wear behaviour. In other words, FFNN model was more efficient, SVR model was efficient and MLR model was inefficient in predicting the wear behaviour of the composites. Figures 4, displayed the fitness of the actual and predicted values in form of scatter plots of the MLR, SVR and FFNN of wear single models, respectively.

Figure 5 provide the scatter plots of the models. In the case of prediction of COF of the glass fibre reinforced PTFE composite, it was found that FFNN model DC (0.9393) with RMSE (0.0456) having a structure of [5-11-1]1 trained by Levenberg-Marquardt (LM) algorithm and SVR model DC (0.9321) with RMSE (0.0453) models were more successful in predicting the COF than MLR model of DC (0.5787) and RMSE (0.1053). As noted the RMSE of SVR in terms of COF is lower than that of FFNN. This disparity can be explained on the basis of the kernel function chosen (RBF) which has the capability to minimize the error of the generalization problem to the barest minimum possible. As mentioned earlier that different learning algorithms perform differently under different circumstances [19], it is seen here that in predicting the COF (new circumstance) of the composite, the learning algorithm for COF is different from that of wear. The reasons for the lower and high prediction performance of SVR and MLR models were as stated in [52] and [53-54], respectively.

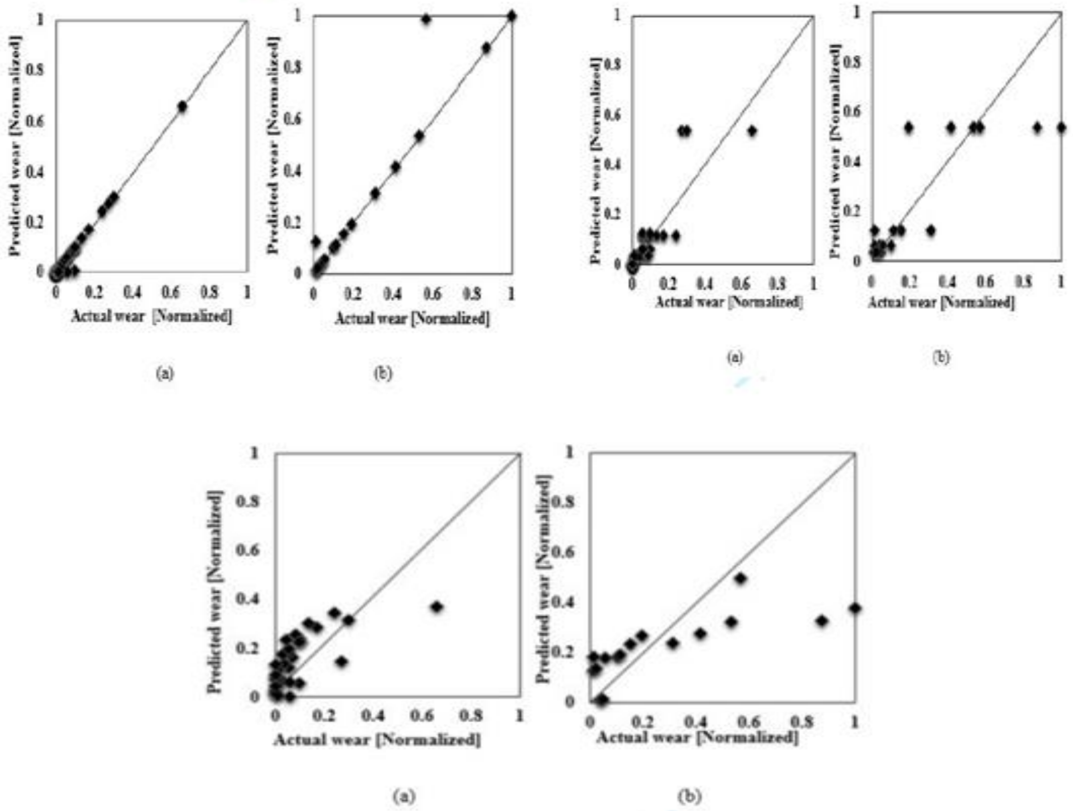


Figure 4 Scatter plots of the FFNN, SVR and MLR of wear single models in (a) training and (b) testing stages of the composites

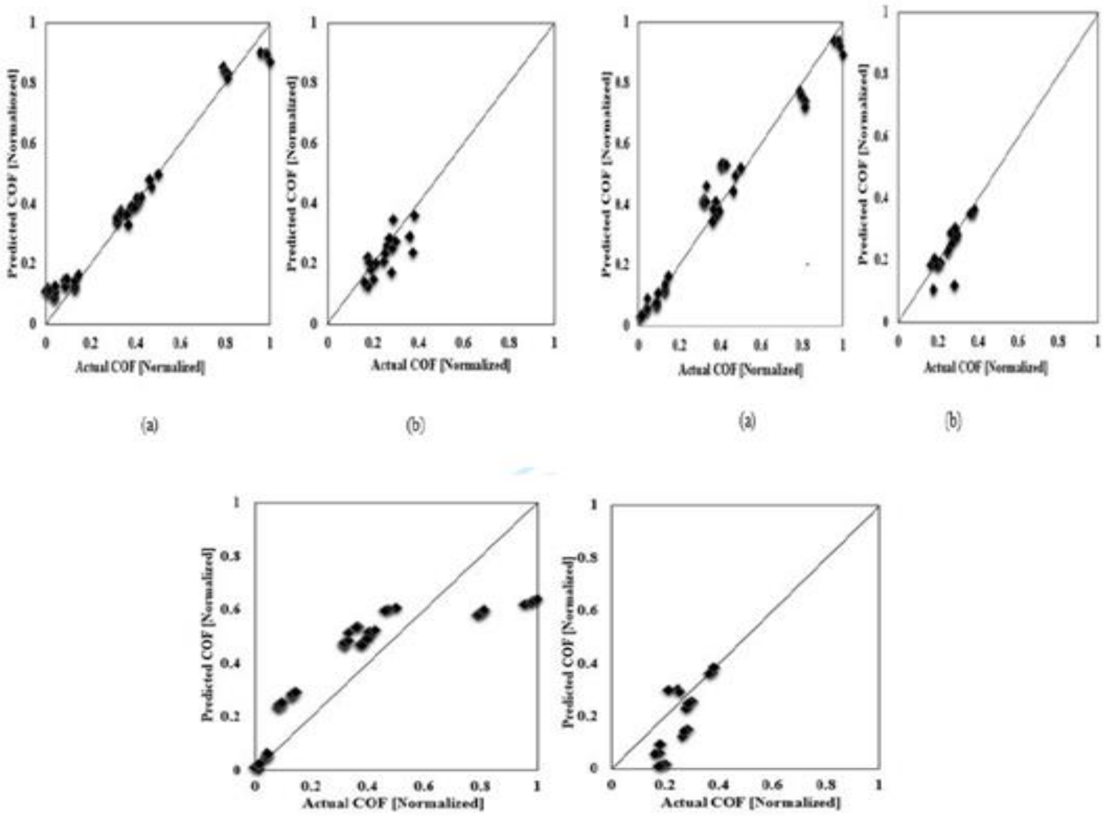


Figure 5. Scatter plot of the FFNN, SVR, MLR of COF single models in (a) training and (b) testing stages of the composites

3.2 Performance of the Ensemble Models

To enhance the prediction performance of the single models, four different kinds of ensemble methods that integrate the advantageous features of each of the individual model were built in the final phase of the modelling. The response factors of the individual models were supplied as input signals to the ensemble separate parts. This section presented the results and discussion of the linear and nonlinear ensemble models.

3.2.1 Performance of Linear Ensemble Models

The linear ensemble models namely WA and SA were modelled through Eq. 15 and Eq.16, respectively. Results of the linear ensemble algorithms for the prediction of the wear (Table 4) as well as COF (Table 5) characteristics of glass fibre reinforced PTFE composites were as provided in the mentioned tables. As observed in Table 4, SA linear ensemble showed DC = 0.8452 and RMSE of 0.1267 while WA linear ensemble indicated DC of 0.8636 and lower RMSE of 0.1200. Similarly, for estimating COF WA linear ensemble indicated higher DC and lower RMSE of 0.9293 and 0.0492, respectively than SA ensemble with DC of 0.9107 and RMSE of 0.0541. Given the above, it can be said that SA and WA models have demonstrated a remarkable increase in the wear and COF characteristics prediction accuracy of the glass fibre reinforced PTFE composites over the single MLR model. This increase in prediction accuracy of the linear ensemble models over the single MLR model is related to the balancing of datasets as well as elimination of random errors due to averaging thus giving better predictions. More so, the WA linear ensemble showed better prediction performance than the SA ensemble. The reason for this could be explained on the basis that WA takes into account frequency of some factors in the dataset as well as weight attached to each data point in the dataset thus soothing out the dataset and enhancing the prediction accuracy. It is evident that the linear averaging of data points in a set often produces magnitude smaller than the biggest magnitude in the set. Figures 6, 7 as well as 8, 9 for wear and COF, respectively showed the scatter plots of SA and WA linear ensemble models.

Table 4. Wear performance of results of the linear ensemble models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
SA	0.8852	0.1102	0.8452	0.1267
WA	0.9091	0.0396	0.8636	0.1200

Table 5. COF performance of results of the linear ensemble models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
SA	0.9327	0.0792	0.9107	0.0541
WA	0.9507	0.0678	0.9293	0.0492

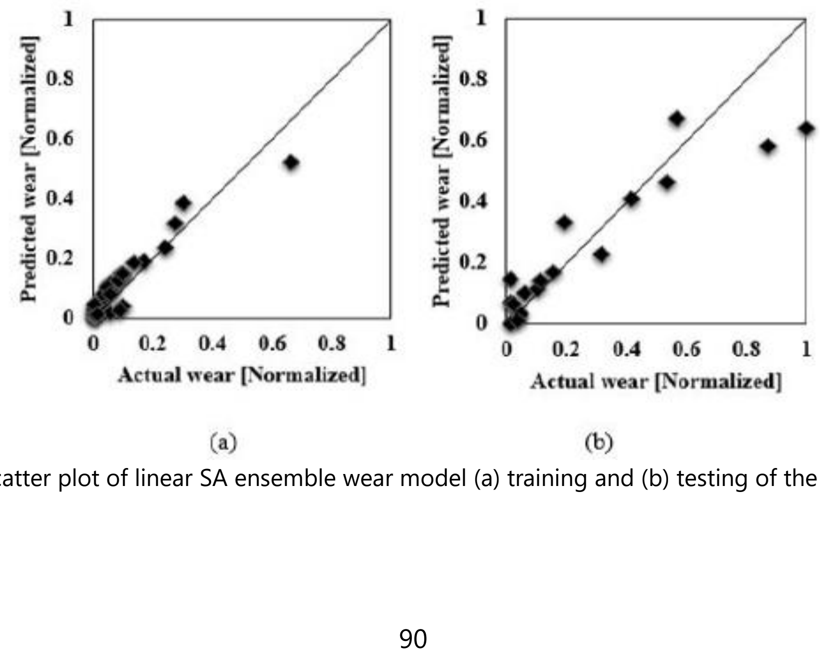


Figure 6. Scatter plot of linear SA ensemble wear model (a) training and (b) testing of the composites

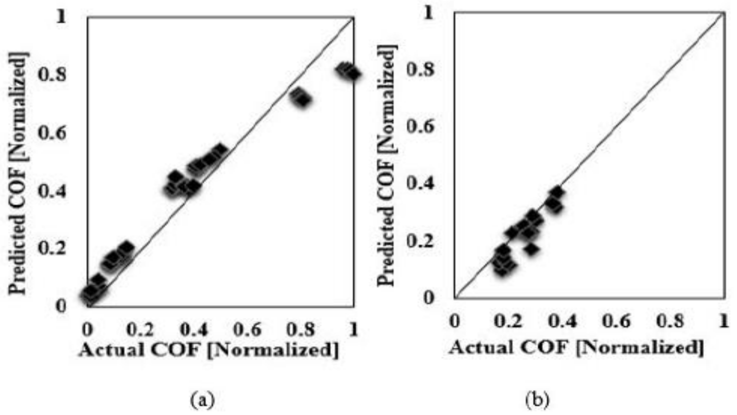


Figure 7. Scatter plot of linear SA ensemble COF model (a) training and (b) testing of the composite

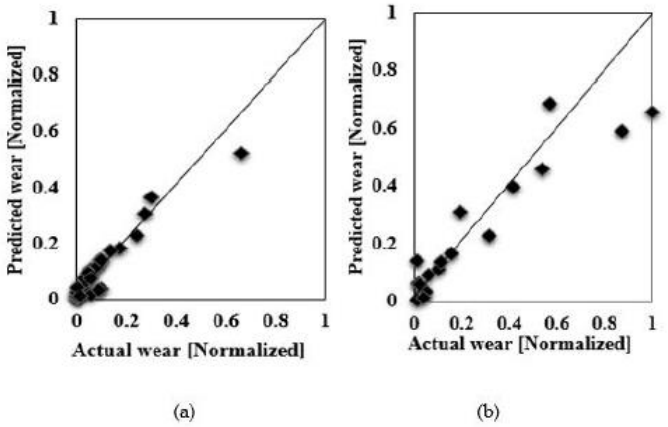


Figure 8. Scatter plot of linear WA ensemble wear model (a) training and (b) testing of the composites

3.2.2 Performance of Nonlinear Ensemble Models

In the nonlinear ensemble units (FFNNE and SVRE), the ideas of FFNN and SVR models were used. For the determination of the optimum number of neuron in the hidden layer Eq. 5 was also applied. The optimum FFNNE architecture for the wear behaviour prediction was found to be $[3\text{-}6\text{-}1]_1$ trained by Levenberg-Marquardt (LM) algorithm while for the COF the optimized FFNNE structure was $[3\text{-}6\text{-}1]_1$ with Bayesian regularization (BR) as training algorithm. The results of the nonlinear ensemble methods were as depicted in Tables 6 and 7 for wear and COF of the PTFE matrix composites, respectively. From Table 6 it was observed that SVRE displayed lower DC of 0.9020 and higher RMSE od 0.1014 as compared to FFNNE having a higher DC of 0.9992 and lower RMSE of 0.0092 in predicting the wear behaviour of the glass fibre reinforced PTFE composites. In other words, an improvement of wear prediction accuracy of 27% and 10% over the SVR and FFNN nonlinear single models was achieved. For COF, the prediction performance in terms of the DC was nearly the same (0.9753 and 0.9798, respectively). However, FFNNE showed the minimum prediction RMSE of 0.0262 in comparison to SVRE with a RMSE of 0.0362. This implies an increase in prediction performance of COF of the glass fibre reinforced PTFE composites by 5% and 4% for FFNN and SVR nonlinear single models, respectively. This enhancement of the prediction performance of the nonlinear single models by the nonlinear ensemble models is attributed to post-data processing technique in which data is processed in parallel can be used to improve on the prediction accuracy of models. The superior performance of the AI models in modelling and prediction of nonlinear situations over the conventional approaches have been proven by NE method.

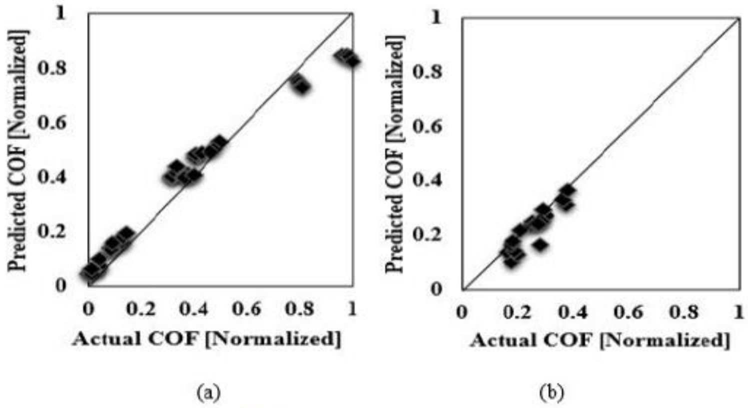


Figure 9. Scatter plot of linear WA ensemble COF model (a) training and (b) testing of the composite

Table 6. Wear performance of results of the nonlinear ensemble models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
SVRE	0.9836	0.0168	0.9020	0.1014
FNNE	0.9809	0.0184	0.9992	0.0092

Table 7. COF performance of results of the nonlinear ensemble models

Used Technique	Calibration		Verification	
	DC	RMSE	DC	RMSE
SVRE	0.9805	0.0427	0.9753	0.0262
FFNNE	0.9964	0.0184	0.9798	0.0362

As seen in Tables 4 and 5, the ensemble method has the potential of enhancing the prediction quality of the single models. The nonlinear ensemble methods have increased the wear prediction performance of the composite of the individual approaches by 45%, 27% and 10% for MLR, SVR and FFNN models, respectively. For COF, the prediction performance of the single approaches was improved by 5%, 4% and 39% for FFNN, SVR and MLR models, respectively. The superior performance of the AI models in modelling and prediction of nonlinear situations over the conventional approaches have been proven by NE method. Figures 6, 7, 8, 9, 10, 11, 12 and 13 depict the nonlinear and linear ensemble approaches for wear and COF of the glass fibre reinforced PTFE composites.

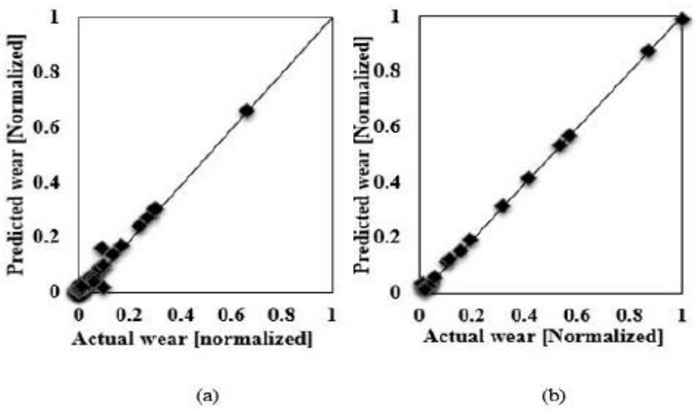
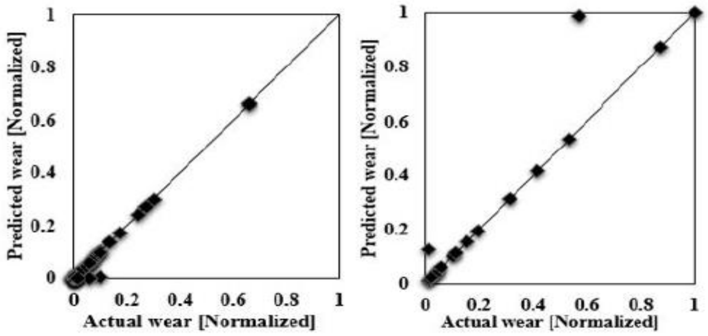
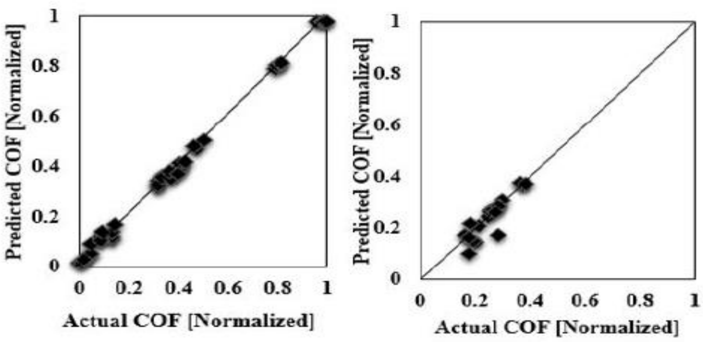


Figure 10. Scatter plot of nonlinear FFNN ensemble wear model (a) training and (b) testing of the composites



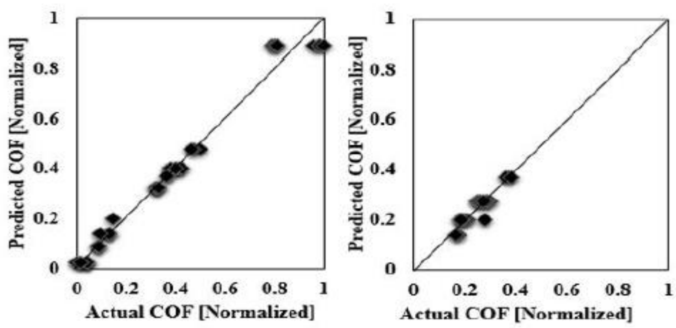
(a) (b)

Figure 11. Scatter plot of nonlinear SVR ensemble wear model (a) training and (b) testing of the composites



(a) (b)

Figure 12. Scatter plot of nonlinear FFNN ensemble COF model (a) training and (b) testing of the composites



(a) (b)

Figure 13. Scatter plot of nonlinear SVRE ensemble COF model (a) training and (b) testing of the composites

3.3 Comparing the Single and Ensemble Models

As seen in Tables 4, 5, 6 and 7, the ensemble methods have the potential of enhancing the prediction quality of the single models shown in Table 2 and 3 for wear and COF characteristics of glass fibre reinforced PTFE composites, respectively. The linear ensemble methods viz: SA and WA have demonstrated a remarkable increase in the prediction accuracy over the single models with the exception of FFFN in the wear prediction of the glass fibre reinforced PTFE composites. This has to do with the ability of the FFNN model to mimic the outside world by means of its make-up. However, in the prediction of COF of the composites, the prediction performance of SA technique was better than MLR model only while WA approach was better than those of MLR and FFNN models but SVR model slightly higher than WA method by 0.72%. The nonlinear ensemble methods have increased the wear prediction performance of the composite of the individual approaches by 45%, 27% and 10% for MLR, SVR and FFNN models, respectively. For COF, the prediction performance of the single approaches was improved by 5%, 4% and 39% for FFNN, SVR and MLR models, respectively.

To further illustrate the comparison of the models, RMSE was of all the models was considered and was depicted in Figure 14. More so, the ensemble methods indicated different prediction accuracy for wear and COF characteristics of PTFE based composites. Based on Figure 14 (a), it was observed that FFNNE nonlinear ensemble outperformed the others models in generalizing wear of the PTFE based composites. In predicting the COF of the glass fibre reinforced PTFE composites, SVRE nonlinear ensemble model (Figure 149b) showed superior performance to other models. This indicates a minimization or reduction in errors by the nonlinear ensemble method. The proposed nonlinear ensemble method as a post-data processing technique in which data is processed in parallel can be used to improve on the prediction accuracy of predictive models. The models can be used to improve the prediction accuracy of single models without complications.

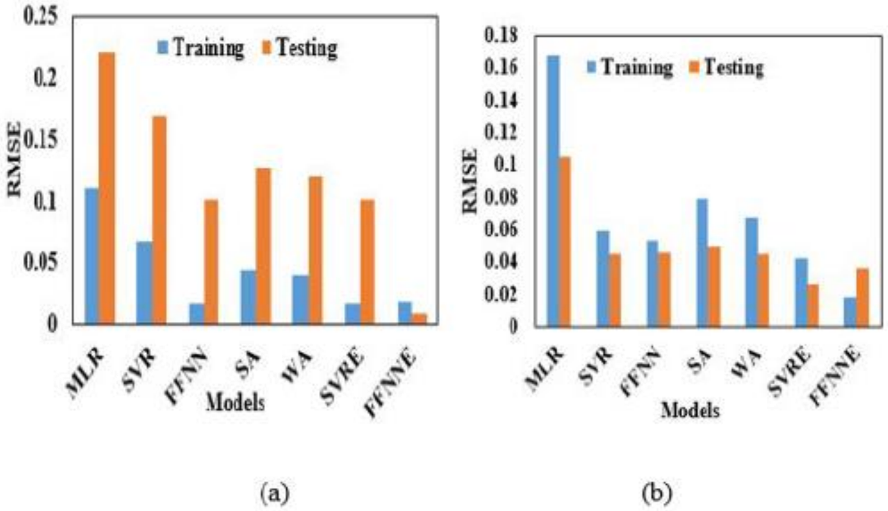


Figure 14. Comparison of RMSE of the single and ensemble models for (a) wear and (b) COF of the composites

4. Conclusions

In this study, prediction of wear and coefficient of friction (COF) of glass fibre reinforced PTFE composites using two AI models namely FFNN and SVR and one traditional MLR model has been performed. Consequent to the building of single black box models, four ensemble methods consolidating the merits of the single models were built to improve the prediction performance of the single as inputs to the ensemble methods. Comparing the results obtained from the single models indicated that SVRE and FFNNE have prediction efficiency for wear and COF, respectively than other models owing to their ability to withstand uncertainties. The ensemble methods enhanced the wear rate prediction adequacy of the single models with nonlinear ensemble methods yielding superior performance to linear ensemble models because of their robustness to handle complex phenomenon such as wear rate. In addition, it was found that the novel ensemble methods have the capacity of increasing the wear rate prediction efficiency of the single MLR, FFNN and SVR models for wear and COF by 45%, 27% and 10% and by 4%, 5% and 39%, respectively. The superiority of the linear ensemble methods outstripped that of the single models except for FFNN that was best among the single models since linear averaging often yields results lower than the highest value within the set. The limitations of the SA linear ensemble methods in the study is that, lower performance of one of the single models may lead to a performance lower than the most robust single model. As noticed in this study, the performance of the linear ensembles is less than that of the FFNN model which is due to lower performance of the MLR model. Only nonlinear ensemble approaches should be used in future studies for providing higher efficiency in the prediction of wear rate of PMCs. Application of other nonlinear model like adaptive neuro-fuzzy inference system for ensemble models may also be explored in future studies.

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